Litigation versus spillovers

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Abstract

This paper studies how patent litigation affects innovation and technology spillovers across firms. Using a unique data set on patent litigation from the United States, this paper shows that litigants are active innovators and share complementary knowledge assets with each other, creating spillovers. However, as a result of litigation, firms reduce follow-on innovation, thus impeding the effects of spillovers. Moreover, litigants fall behind the frontier, resulting in a divergence of productivity growth, which suggests a reduction of their role as intermediaries of knowledge diffusion. These findings imply that litigation, in contrast with the original objective of the intellectual property rights (IPRs) enforcement systems, can obstruct technological diffusion, which not only decreases cumulative innovation and spillovers, but also slows down productivity growth.

JEL codes: G32, K41, K42, O33, O34, O36, O47
Keywords: Patent, Litigation, Innovation, Knowledge diffusion, Technology distance, Intellectual Property Rights, Productivity

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1 Introduction

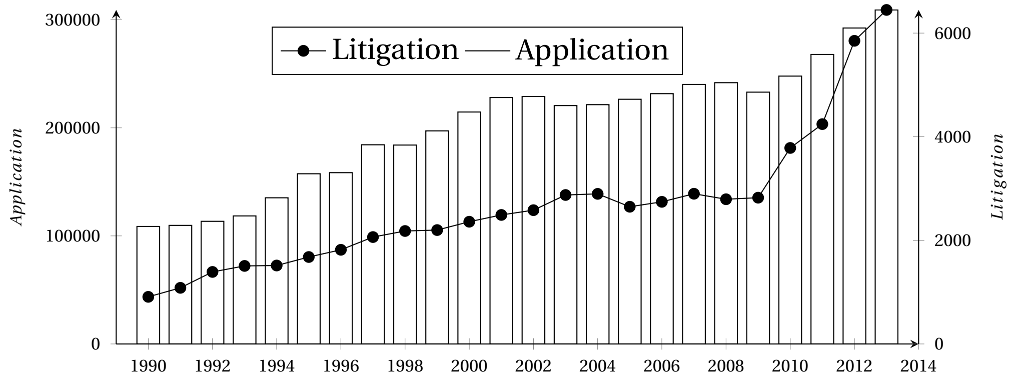
In a knowledge economy, intangible assets become more important than ever (Corrado et al. 2009; Corrado and Hulten 2010). In addition, digital transformation and international trade have accelerated the use of knowledge assets. However, contrary to the expectation that increased amount and speed of knowledge flow would cause economies to converge, several OECD and non-OECD economies have experienced the opposite: the gap in wages and productivity have increased among firms over the last three decades (Berlingieri et al. 2017).

Among the multiple explanations for this increased dispersion, Akcigit and Ates (2019) highlight that a reduction in spillovers might be the main cause: slow knowledge diffusion can explain several empirical trends in the global economy, including the divergence in productivity between the frontier and others (Andrews et al. 2016), and high market concentration (Autor et al. 2019). In line with several attempts to answer this question, this paper provides new direct evidence of a decline in knowledge diffusion, using patent litigation data from the United States, and finds that litigation reduces the follow-on innovation of litigants and reduces their role as intermediaries of knowledge diffusion.

Over the last thirty years, we have witnessed a continuous increase in the number of patent applications. At the same time, the number of patent litigation cases has tripled, as shown in Figure 1. Intellectual property (IP) infringement and spillovers have subtle boundaries. As ideas are non-rival and can move freely, many firms use knowledge assets without knowing to whom those assets belong. In addition, the non-excludable nature of such assets makes it hard to disentangle infringement from spillovers. Therefore, litigation to protect IP assets against infringement plays an important role. Firms benefit from spillovers and "complementary knowledge," especially when they share similar characteristics, such as technologies, products and production facilities. At the same time, however, increased conflict of interest and competition over complementary knowledge can lead to a high probability of IP infringement.

When it comes to business performance, the impact of litigation can be significant. To survive, firms must enhance their productivity, increase their values, and further contribute to economic spillovers (Romer 1986; Aghion and Howitt 1992). Yet, in the case of IP infringement, courts can order a complete injunction on the business or impose extremely large compensations for the loss of profit – not to mention the time and cost of legal procedures. In the last 30 years, litigation costs have amounted to USD 300 billion (Bessen and Meurer 2013) and indirect costs resulting from litigation might be multiple times higher than that. And, once the negative impact on knowledge diffusion is taken into account, the full economic cost and the negative impact of litigation on an economy as a whole become even more severe.

Figure 1: Trends in patent application and litigation



(Own calculation, source: United States Patent and Trademark Office (USPTO)

In this paper, therefore, to find the impact of litigation on spillovers, I examine ex ante and ex post litigation by focusing on the use of complementary assets, defined as knowledge assets that create spillovers, such as patents. This paper makes two main contributions. In the first part, I show that ex ante litigants are active innovators at the frontier and share complementary knowledge assets. I find that spillovers driven by complementary assets increase the likelihood of litigation, while litigation reduces complementary spillovers and follow-on innovation. This issue has not been fully explored in the literature, although complementarity is indeed the prerequisite of patent litigation. For this research, I construct measures of *Technology Proximity* between plaintiffs and defendants that allow me to identify the close relationships between firms involved in litigation. In addition, I examine the direction and degree of changes that arise after litigation and show that total innovation activity contracts (scale effect) and that patenting activity moves from the litigation-related field to other fields (substitution effect), which impedes successive innovation and distorts patenting behaviors.

In the second part, I try to answer a fundamental question about the productivity slowdown of the U.S. economy. After showing that litigation results in a decline of knowledge spillovers, I find that the decrease in patenting activity and citations reduces a firm's role not only as an innovator but also as an intermediary of knowledge diffusion through spillovers. In addition, I also find that litigation reduces firms' productivity and the values of their intangible assets. To understand the relative performance of litigants, I examine how litigation shapes the distance between plaintiff-defendant and firms at the frontier. The second main finding of the paper is that both plaintiffs and defendants fall behind the frontier in terms of both innovation and productivity, suggesting that litigation imposes a high cost on both opponents. Given that technology diffusion occurs by linking innovating leaders and imitators (Jovanovic and Macdonald 1994), this finding provides a novel additional channel for understanding how reduced technology spillovers can affect productivity slowdown and how changes in patenting strategy reduce competition between neck-and-neck firms, thus reducing innovation (Aghion et al. 2005).

In order to understand the characteristics of litigation, I create a unique patent litigation data set, matching the United States Patent and Trademark Office (USPTO) data set with Compustat and USPTO. I construct case-firm-year level panel data for plaintiffs, defendants, and firms in the control group to examine the impact of litigation on various spillover measures. This rich data set allows me to study the impact of litigation from various angles, including firm innovation and financial characteristics. Using the difference-in-difference approach, I show the ex ante and ex post performance of firms and identify that spillovers are one of the most important triggers for litigation, particularly when the spillovers become intense and overlap with the knowledge property of others. To show that the results are robust, I conduct a dynamic trend analysis to confirm that the use of the complementary assets intensifies until litigation and then decreases afterward. I further show that these results do not replicate when a placebo litigation year is imposed.

I identify that at the microeconomic level, spillovers are one of the most important triggers of litigation, particularly when spillovers become intense and overlap with the knowledge property of others. Moreover, by constructing indexes to measure magnitude and intensity, I find that litigation harms knowledge spillovers by reducing innovative activities as well as changing a firm's technological directions. Similarly, to explore the impact on an overall economy, I explore how the litigant's role changes the plaintiff–defendant–frontier relations. I show that firms that used to actively innovate at the technology frontier fall behind their rivals and become less innovative and more strategic. This results in a reduction of a firm's cumulative innovation in technology sectors related to the litigation and eventually harms the firm as well as the overall economy.

This paper contributes to the literature in several ways. First, by highlighting the negative effects of patent litigation on spillovers, it provides new empirical evidence on the long-standing debate over the reasons for the productivity slowdown of the United States. A large body of literature has documented several explanations surrounding this concern: market concentration (Autor et al. 2019), mark-up (De Loecker et al. 2020), and productivity gap (Decker et al. 2018), among others. In line with Akcigit and Ates (2019), this paper proposes that a reduction in knowledge diffusion is one of the main drivers of the decline in economic growth. For example, geographical proximity (Porter 2000), the regulatory framework (Grullon et al. 2019), and IT intensity (Calligaris et al. 2018) may be factors explaining this macro economic issue. This paper adds a new explanation by investigating the litigation channel, which affects knowledge diffusion in important ways. Thus, this paper raises the following concern: instead of promoting knowledge diffusion and stimulating innovation, litigation actually reduces innovative endeavors at the leading edge of the innovation frontier.

Second, this paper contributes to endogenous growth literature. Since innovation is key to economic growth, firms tend to collaborate on new ideas and advance the technology frontier (Aghion and Howitt 1992). This paper supports the idea that technology diffusion occurs through innovation and links innovating leaders with imitators (Jovanovic and Macdonald 1994; König et al. 2016). A large amount of previous work has focused on positive spillovers with externalities, showing various forms of interactions among firms. However, this paper, while in line with the idea that firms acquire new knowledge by searching and interacting (Lucas and Moll 2014; Perla and Tonetti 2014), also looks at the competitive side, where there exists a high degree of spillover intensity and conflicts of interest. Spillovers have been mainly studied in indirect ways, such as R&D spillovers through contacts among scientists (Bloom et al. 2013), co-movement of stock returns (Fung 2003), or open innovation (Chesbrough 2003). In contrast, only a few studies directly have measured the impact of events such as M&A (Bena and Li 2014), purchase of patents (Akcigit et al. 2016), or R&D outsourcing (Buss and Peukert 2015). My paper provides direct evidence based on the special feature that litigation requires a burden of proof that the use of IP assets exists.

Third, this paper complements IPRs literature in several ways. Firstly, it extends the literature on what determines litigation. Current literature focuses mainly on the characteristics of patents under litigation, highlighting the importance of invention (Lanjouw and Schankerman 2001), or on how a firm's characteristics affect either the probability of litigation or litigation results (Bessen and Meurer 2013). In contrast, this paper focuses on the relationship between firms, particularly the use of complementary assets and the firms' proximity in the technology space, a relationship that has been underexplored. Secondly, while the role of a patent has been frequently studied and criticized, the impact of patent litigation is less well-known (Galasso and Schankerman 2015, Bessen and Maskin 2009), even though litigation is more important in protecting an inventor's motivation. There have been only a few works that study the impact of litigation (Smeets 2014; Lee et al. 2018; A. Marco et al. 2015). Thirdly, this paper, although in line with literature that litigation reduces follow-on innovation, differs by focusing on whether litigation helps to promote knowledge diffusion. Furthermore, my paper tries to extend a possible explanation of defensive activities (Hall and Ziedonis 2001; Cohen et al. 2019) by finding scale and substitution effects based on various firms' strategic behaviors. Fourthly, this paper fills the gap by investigating litigation among practicing entities. Whereas recent literature focuses on the strategic litigation filings of NPEs (Council of Economic Advisers 2016; Cohen et al. 2019; Scott Morton and Shapiro 2014; Mezzanotti 2017), this paper proposes that litigation among practicing entities can distort competition and even harm innovation further. Thus, I call for policies to refine the IPRs enforcement systems, to improve the function of market competition, especially with complex knowledge assets.

Fourth, this paper proposes a novel approach in terms of methodology. By using large and unique plaintiffs-defendants litigation data sets from the United States and creating case-litigant-control matched samples, this paper empirically examines how litigation influences both plaintiffs and defendants. Lastly, this paper complements law and economics literature by providing empirical evidence, mainly based on a qualitative analysis due to the absence of data (Shaver 2012).

This paper is organized as follows: Section 2 develops the conceptual framework. Sections 3 and 4 introduce data and how key variables are constructed. Section 5 introduces empirical strategy. The first part of the findings is presented in Section 6. the second part is presented in Section 7. Finally, Section 8 concludes.

2 Conceptual Framework

I consider a symmetric oligopoly (Harhoff et al. 2003; Meurer et al. 2005) where all firms produce a same product and earn profit of G_0. There exists spillovers among firms. A firm compares its expected profit from investing innovation directly to the profit from spillovers, indirect externality from innovation. An innovating firm can file a patent infringement suit in case of infringement of firms' intellectual property (Lanjouw and Lerner 1997) in relation to innovation. An innovating firm compare expected profit from going to trial to the profit of non litigation.

At stage 1, a plaintiff, firm P, decides whether to innovate. If firm P innovates with R&D expenses r, firm P can hold a patent and increases profit by G_1 by opening a new market and the profit becomes:

$$\pi_P = G_0 + G_1 - r$$

At state 2, firm D decides whether to use the innovation of firm P. If firm D does not use the patent of firm P, then the profit of firm D remains G_0.
However, firm D decides to use the patent of firm P, then firm D can take the profit of the innovator by $\lambda \mathrm{G}_1$ with $\lambda \in [0, 1]$.

λ denotes the intensity of spillovers. When $\lambda = 0$, the innovation is perfectly protected by Intellectual Property Rights Enforcement Systems and there exists no spillovers. When $\lambda = 1/2$, there is no protection and innovation can be used freely. Intellectual Property infringement is increasing in spillovers λ but there does not exist clear thresholds.

Therefore, the profit of firm D becomes $\mathrm{G}_0+\lambda G_1$. while the profit of firm P is reduced by λG_1 The profit of firm P and firm D becomes as follows:

$$\pi_P = G_0 + (1 - \lambda)G_1 - r$$
$$\pi_D = G_0 + \lambda G_1$$

At stage 3, firm P can choose whether to file a suit against firm D . If firm P does not litigate, the profit of firm P remains:

$$\pi_P = G_0 + (1 - \lambda)G_1 - r$$

If firm P files a litigation, with a winning probability α, firm P recovers $G_0 + G_1$. If firm P loses with a probability of (1-α) and profit becomes $G_0 + (1 - \lambda)G_1$. On the other hand, if firm P wins the case, the firm receives the compensation J. If firm P litigates, regardless of the results, both firms P and D have to pay the legal cost C.

Therefore, I can express the expected profit of litigation as follows:

$$Exp(\pi) = \alpha\underbrace{[G_0 + G_1 - r - C + J]}_{\text{win the case}} + (1-\alpha)\underbrace{[G_0 + (1-\lambda)G_1 - r - C)]}_{\text{lose the case}}$$

2.1 Probability of Litigation

Firm P file a suit only if litigation profit is higher than non-litigation profit:

$$\alpha[G_0 + G_1 - r - C + J] + (1-\alpha)[G_0 + (1-\lambda)G_1 - r - C] > G_0 + (1-\lambda)G_1 - r$$

This inequality describes the parameters that affect the probability of litigation. By rearranging the equation, the probability of a litigation becomes:

$$\alpha(\lambda G_1 + J) - C > 0$$

Thus, the probability of litigation is determined by profit of firms using innovation, and cost and benefit incurred by litigation. The function can be expressed as a following function:

$$\textit{Pr(Litigation)} = F(G_1, \lambda, \alpha, J, C) \tag{1}$$

Therefore, I derive the hypothesis of the consequences of the probability of patent litigation as follows:

Hypothesis 1: The probability of patent litigation increases with the intensity of spillovers. when λ is greater, the reduction of a plaintiff's profit becomes larger, therefore a plaintiff is likely to file a litigation.

The probability of litigation increases when G_1 is greater as shown in the literature. In addition, the probability also increases with the probability of winning litigation, compensation amount J and decreases in legal cost C.

2.2 Probability of Innovation

Now, I go back to the initial stage, firm P can choose whether to innovate given the possibility of being infringed by other rival firms.

I assume that the probability of spillovers/or infringement that other firms use the patent of firm P is β, then we can think that β increases in λ.

I can express the expected profit of innovation as follows:

$$Exp(\pi) = \beta\underbrace{[G_0 + (1-\lambda)G_1 - r]}_{\text{spillovers}} + (1-\beta)\underbrace{[G_0 + G_1 - r]}_{\text{No spillovers}}$$

Firm P innovates only if the profit with innovation is larger than the profit without innovation.

$$\beta[G_0 + (1-\lambda)G_1 - r] + (1-\beta)[G_0 + G_1 - r] > G_0$$

By rearranging the equation, the following equation can be derived and the probability of a litigation becomes as follows:

$$G_1(1-\beta\lambda) - r > 0$$

$$\textit{Pr(Innovation)} = F(G_1, \beta, \lambda, r) \tag{2}$$

Therefore, I derive the hypothesis of the consequences of the probability of innovation as follows:

Hypothesis 2: The probability of patent innovation decreases with the intensity of spillovers. when λ is greater, the reduction of a plaintiff's profit becomes larger, therefore a probability of innovation decreases. Similarly, the probability of innovation decreases in β. That is, if the probability that other firms use the innovation of a plaintiff increases, the probability of innovation decreases.

On the other hand, the probability of innovation increases with the quality enhancement by new innovation Q_1 and decreases in R&D cost r.

3 Data

3.1 Data Collection

In this paper, I use four data sources to measure litigation impact. To identify litigant firms, I use the United States Patent and Trademark Office (USPTO) Docket Report Data

1. The USPTO data does not include final verdict information. However, Lee et al. (2018) find that 1) only 18% of patent litigation reached a final verdict, 2) plaintiffs had a 64% winning rate, and 3) 70% of cases are dismissed after being filed. Similarly, Pwc (2017) provides that patent holders had a 66% success rate at trials from 1997 to 2016.

(Marco and Tesfayesus 2017) and then match them to U.S. Compustat for financial variables and USPTO PatentView for technological attributes.

The historical patent litigation data released by USPTO in 2015 contains litigation party types (plaintiffs and defendants), date filed and closed, [1], attorneys, court information and patent assignments (Schwartz et al. 2019).[2] The litigation data provides only firm names and addresses. Therefore, I develop a name standardization matching procedure: I clean firm names, I remove suffixes, and I unify name patterns to have a more common corporate name format. As a next step, I apply the name cleaning methodology suggested by the NBER patents community. Then, I match firms that exactly match names in two data sets. Among litigants, I only keep litigation cases where both litigants are covered by Compustat from 1995 to 2015. I remove small firms, firms in the financial sector (SIC 6000-6999), and regulated firms (SIC 4900 - 4999). Although Compustat only covers publicly listed firms, the sample covers litigants relatively well because R&D is heavily concentrated on listed firms (Bloom et al. 2013).

While using litigation data, one may be concerned about the timing of litigation. I acknowledge that, at least for plaintiffs, the timing of litigation can be self-selected.[3] A plaintiff who changes her own patent portfolio may decide to file a suit against a defendant when the plaintiff is no longer interested in the collaborative relationship.

I try to fix this issue by, firstly excluding Non Practicing Entities (NPE) who act in a more strategic way in litigation. By using Compustat, these firms are naturally removed. Then, using the list of the NPE database from Stanford Law School (Miller 2017), I exclude all possible candidates for such strategic use. In addition, I use fixed effects to control observable characteristics and conduct robustness tests in Section 6.4 .

Lastly, I use PatentsView bulk download data, which contains detailed information on three million U.S patents granted between 1963 and 2016, and all citations made to these patents between 1963 and 2016. Firms with zero patents are dropped at this stage. As a result, my final sample includes litigation information and financial and innovation information at firm-year level.

3.2 Descriptive Statistics

I focus on the litigating firms compared to all other firms that are active and engaged in innovation activities. Table 1 presents summary statistics of litigants compared to all firms covered by both Compustat and PatentsView.

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2. Among 120,840 patents in total, 45,596 unique patents have patent number information for the periods 2003-2016. Hence, the analysis using patent ID in this paper is limited to this period.

3. The reports of the USPTO also acknowledge that when analysing the litigation, it is required to take into consideration the issue of self-selection. In using litigation information, "There must happen a dispute, and secondly, the dispute should not be settled before reaching a formal process. Lastly, only a few cases reach at the final decision.(A. C. Marco et al. (2015))

Table 1: Summary statistic: Firms average vs. Litigants

	Mean	St Dev.	Min	Median	Max	N
All firms						
Assets	5.13	2.39	0.93	4.83	12.14	36676
Sales	4.78	2.56	0.00	4.70	11.52	36623
R&D	2.20	1.54	0.00	2.02	9.11	27872
Total Citations	2.70	1.62	0.69	2.40	9.68	26621
Total Patents	6.53	1.54	4.61	6.40	12.82	26621
Defendants						
Assets	7.18	2.46	0.93	7.32	12.14	1745
Sales	6.87	2.60	0.00	7.09	11.52	1743
R&D	4.43	2.30	0.00	4.35	9.11	1632
Total Citations	5.58	2.55	0.69	5.71	11.18	1254
Total Patents	9.31	2.47	4.61	9.31	15.08	1254
Plaintiffs						
Assets	6.96	2.66	0.93	7.02	12.14	1600
Sales	6.55	2.80	0.00	6.74	11.52	1599
R&D	4.49	2.41	0.00	4.34	9.11	1534
Total Citations	5.84	2.24	0.69	6.09	11.22	1275
Total Patents	9.52	2.19	4.61	9.68	15.10	1275

Note: This table presents summary statistics for both litigant firms and firms not engaged in litigation that are active and engaged in patent activity. The data are provided by Compustat and Patstat. The middle and bottom panel show statistics for defendants and plaintiffs, respectively. All the variables are calculated in log term. Average values of preceding three years before litigation are used. Assets, sales and R&D are measured in millions of dollars and expressed as log values

As shown in table 1, firms that have experienced litigation are bigger in size both in terms of assets and sales. Similarly, R&D investment is much higher for firms involved in litigation. On average, R&D investment is 4.49 (expressed in log term) and 4.43 for plaintiffs and defendants respectively, whereas it is only 2.20 for firms on average. In terms of the innovation index, litigant firms on average have more patents, and receive twice as many patent citations. This suggests that both plaintiffs and defendants are located in the right tail of firm distribution in the economy.

4 Main variables

Knowledge is transferred between firms when they are exposed to each other and the intensity depends on the proximity of the fields in which firms operate (Bloom et al. 2013). To measure the relatedness, I use two different methodologies to verify the proximity between firms. I focus, first, on innovation characteristics based on technology similarity, and, second, based on *Patent Overlap* measures using patent citations.

4.1 *Technology Proximity* Measures

4.1.1 Technology Proximity between Plaintiffs and Defendants

To measure the relatedness, I construct the proximity index, *Technology Proximity*$_{p,d}$ between pairs of plaintiffs (p) and defendants (d), following Jaffe (Jaffe 1986; Bloom et al. 2013; Fons-Rosen et al. 2017; Bena and Li 2014). This approach measures potential technology spillovers from the R&D of firms in all of that firm's activity areas. A Firm i is engaged in n number of fields and has a number of patents in each technology class. The share of patents per firm i at time t in each technology class n can be expressed in vector $T_{i,t} = (T_{i1,t}, T_{i2,t}, \ldots, T_{in,t})$. Using standard Jaffe cosine similarity index, the proximity measure can be transformed to one index. The calculation of *Technology Proximity* between two firms, a plaintiff and a defendant, can be shown as below:

$$\textit{Technology Proximity}_{p,d,c,t} = \frac{(T_{p,c,t}T'_{d,c,t})}{(T_{p,c,t}T'_{d,c,t})^{(1/2)}(T_{p,c,t}T'_{d,c,t})^{(1/2)}}$$

where pd is a pair of plaintiffs p and defendants d, c denotes a case, t denotes a year. T is a vector of numbers of awarded patents in each technology class.

4.1.2 *Technology Proximity* between litigants and technology under litigation

Distance between plaintiffs and defendants indicates degree of closeness between two firms' portfolios. However, it does not provide their absolute positions in the technology dimension. Therefore, I measure how closely a firm stands compared to the technology class of litigation, which is a fixed point and does not change across the year. This measure presents the absolute distance between a firm and the technology under litigation. This measure is calculated in an analogous way to the *Technology Proximity* measure between pairs as below:

$$\textit{Technology Proximity}_{p(d),LP,c,t} = \frac{(T_{p(d),c,t}T'_{LP,c,t})}{(T_{p,c,t}T'_{LP,c,t})^{(1/2)}(T_{p(d),c,t}T'_{LP,c,t})^{(1/2)}}$$

where *p(or d)* is a plaintiff (or a defendant), *LP* denotes the technology class of patents under litigation, *c* denotes a case, and *t* denotes a year .

This index in particular provides the direction of a firm's technology investment. If the proximity between litigants and a technology under litigation decreases after the litigation, it suggests that a firm engages in less innovation in that litigation-related technology sector.

4.2 Patent Citation Overlap measures

Patent citations show knowledge flow, as well as links between inventions, inventors, and assignee along time and space (B. Hall et al. 2000). Firms in close technology spaces share related technologies externally and internally and they cite prior works. Therefore, citations are the best proxy to measure the complementarity use of knowledge assets, and diffusion of such knowledge among involved parties.

4.2.1 External Overlap

External overlap measures the extent to which two firms base their innovation activities on the same underlying body of knowledge. Firstly, knowledge overlap between a pair of firms can be measured as the total number of common antecedent patents from 3rd party firms (Bena and Li 2014). Knowledge overlap can be counted as the number of patents cited simultaneously by both plaintiffs and defendants.

Then, the External overlap is scaled by each firm's total number of patents in order to reflect the importance of shared knowledge relative to total stock of knowledge of either plaintiffs or defendants. *External overlap* can be calculated as below:

$$External\ Overlap_{p(d),c,t} = \frac{Knowledge\ overlap_{p,d,c,t}}{N_{p(d),c,t}}$$

where $Knowledge\ overlap_{p,d,c,t}$ denotes the number of patents from 3rd party firms cited by both plaintiffs and defendants, *N* denotes the number of patent application, *p(or d)* is a plaintiff (or a defendant) of a pair, *c* denotes a case, and *t* denotes a year .

4.2.2 Cross Overlap

This index shows the extent a litigant uses the opponent's knowledge in litigation. This measures directly the complementarity between plaintiffs and defendants. *Cross Overlap* is calculated using total number of citations in which each party directly cites the other party in its patent application.

The calculation for plaintiffs (defendants) *Cross Overlap* can be shown as below:

$$Cross\ Overlap_{p(d),c,t} = \frac{Cross\ citation_{p(d),c,t}}{N_{p(d),\ c,\ t}}$$

where *Cross Citation* is total number of patents in which plaintiffs (defendants) cite any of defendants' (plaintiffs') patents. *N* denotes total numbers of patent application, *p(d)* is a plaintiff (or a defendant) of a pair, *c* denotes a case and *t* denotes a year.

4.2.3 Self Overlap

Self Overlap measures the extent to which firms depend on their own knowledge base. This index indicates the intensity of a firm's ongoing innovation activities. The calculation of *Self Overlap* can be shown as below:

$$Self\ Overlap_{p(d),c,t} = \frac{Self\ citation_{p(d),c,t}}{N_{p(d),\ c,\ t}}$$

where *Self citation* is the number of patents that a plaintiff (or a defendant) cites of its own previous patent. *N* denotes the number of patent applications, *c* denotes a case, and *t* denotes a year.

4.3 Differences in Technology Proximity and Patent Overlap measures

The above two indexes represent firms' relative positions based on their knowledge assets, but these two measures deliver different information on firms' technology development. The *Technology Proximity* measures represent firms' overall portfolios in the technology dimensions. This index gives a general idea of how they are alike across diverse technologies. On the other hand, the *Patent Overlap* measures indicate their direct relationship between producing innovation and how many complementary assets they share. In addition, proximity measures are based on patents that are granted at year t while *Patent Overlap* measures are calculated based on patents applied at year t. Therefore, *Patent Overlap* measures indicate their active innovation performance while the *Technology proximity* measures represent a firm's overall portfolio already built. More importantly, in terms of complementary relations between plaintiffs and defendants, *Patent Overlap* measures focus on mutual relationships, while proximity measures take into account a firm's acquired patents, regardless of involvement with litigation.

In summary, these measures are important to map where firms stand in technology space from a topological point of view. In particular, these measures allow us to trace the use of complementarity of knowledge assets at year level and reveal the change in intensity of that complementarity.

5 Empirical strategy

My analyses are composed of three parts. In part 1, I identify who becomes litigants. I examine the likelihood that a pair of firms will engage in litigation based on complementary characteristics. In part 2, I examine how the use of complementary assets changes as a result of litigation. In addition, I identify the direction and magnitude of a firm's technology after litigation. In part 3, I provide the link to explain how patent litigation results in a decline of knowledge diffusion in the economy, focusing on litigants' productivity slowdown and their impact on the economy in delivering knowledge.

5.1 Ex ante litigation : Who becomes litigants

I argue that litigation occurs based on the plaintiff-defendant relationship. Patents under litigation generally create greater knowledge spillovers. Lanjouw and Schankerman (2001) find that the characteristics of patents that have gone through litigation involve major inventions. Moreover, if patents involve more firms and claims, there more likely exists an overlap in the firms' interests and, thus, conflicts of interest. Therefore, complementarity proxied by the two aforementioned indexes is the important factor in determining litigation.

Furthermore, as to the decision to go to the trial, firms would consider two factors: value of a patent and their probability of winning compared to their opponent's. These two factors can be measured in a relative relationship, such as to size difference or to the market share attached to the patent. Therefore, I develop how firms determine whether to file litigation based on the pairwise relationship. I use the conditional logit model to assess who becomes defendants or plaintiffs (McFadden et al. 1974, Dyck et al. 2010). For each litigation case, I compare the pair between plaintiffs and defendants and other control pairs between litigant and other firms. All values are calculated using average values between *t-1* and *t-3* when *t* is a litigation year.

$$\begin{aligned} Litigation_{i,c,t} = \beta_0 &+ \beta_1 Firm\ Innovation\ Characteristics_{i,c,t-3,t-1} \\ &+ \beta_2 Firm\ Financial\ Characteristics_{i,c,t-3,t-1} \\ &+ \beta_3 Complementarity_{i,c,t-3,t-1} \\ &+ \epsilon_{i,c,t}. \end{aligned} \tag{3}$$

where $Litigation_{i,c,t}$ equals 1 when i is a plaintiff-defendant pair and 0 for pairs between a litigant and other firms. $\epsilon_{i,c,t}$ is an error term. *Technology proximity* measures and *Patent Overlap* measures are included to capture complementarity. Innovation characteristics are measured using the number of patents and R&D investment, and for financial characteristics firm size and market value are considered.

5.2 Ex-post: Impact of litigation

I identify the impact of litigation by using difference-in-difference regression techniques. To find the impact of litigation, I examine the impact of litigation, in particular the use of complementarity assets between litigants, and each firm's innovation strategy and productivity.

My main difference-in-difference analysis is as below:

$$\begin{aligned} Y_{p(d),c,t} = \beta_0 &+ \beta_1 Treat_{p(d),c,t} \times Post\ Litigation_{p(d),c,t} \\ &+ \beta_2 Treat_{p(d),c,t} + \beta_3 Post\ Litigation_{p(d),c,t} \\ &+ \alpha_i + \theta_c + \delta_t + \epsilon_{i,c,t} \end{aligned} \tag{4}$$

where Y is dependent variables. The *Treat* variable equals 1 when $p(d)$ is a plaintiff-defendant pair, and 0 when $p(d)$ is plaintiffs or defendants-control pair. α_i, θ_c and δ_t represent firm, case and year fixed effects respectively.

I conduct two parallel analyses for two treatment groups: firstly, for plaintiff-defendant-case-year level and, secondly, for defendant-plaintiff-case-year level. For a plaintiff, treatment group equals 1 when the pair of firms is a plaintiff and a defendant, and 0 when the pair of firms is a control and a defendant. Likewise, for a defendant, the treatment groups are pairs of defendant and plaintiff whereas control groups are pairs of controls and plaintiffs. For each case, for a pair of a plaintiffs and a defendant, two separate control groups are constructed. For example, for a plaintiff, control firms are matched based on characteristics more in common with the plaintiff than with the defendant. After selecting controls matched for a plaintiff or a defendant, *Technology Proximity* and *Patent Overlap* measures are calculated for possible combinations of firms to understand pairwise relationships.

5.2.1 Construction of control group

In order to make a precise comparison of the impact of litigation, control groups should be selected with caution. I construct three control groups for the main difference-in-difference analysis. In particular, for a better reflection of the event, I choose the relevant control group at case-plaintiff-defendant level. For each case, control groups are selected for a plaintiff and a defendant respectively. To construct control groups for the plaintiff, control firms are selected that have similar financial and innovation characteristics as the plaintiff.

Secondly, I perform the propensity score matching (PSM) method (Rosenbaum and Rubin 1983; Executive Office of the President 2013) to choose control groups. There is an advantage to using PSM because it not only overcomes the self-selection bias but also creates balanced data sets. Moreover, my matching variables are more robust than the ones suggested by Executive Office of the President (2013) since I impose more rigorous matching rules: I require that year and technology class should be exactly matched.

For control groups 1 and 2, I use PSM to select firms that have the same likelihood of being litigants as defendant firms do. I conduct a logit regression to predict the likelihood of becoming plaintiffs/defendants based on key variables. Then, using propensity score estimates, I construct the control groups using radius matching. As key variables, control group 1 is constructed based on firm size and innovation characteristics such as propensity to patent and total number of patents. Control group 2 considers innovation characteristics only. In this matching procedure, I strictly impose an exact match of year and technology classification to control possible bias. Lastly, control group 3 is composed of five randomly selected firms in the same technology classification. Throughout my analyses, I show the results using all three samples. Ideally, my most accurate results are from control group 1.

5.3 Sample overview

The main sample consists of plaintiff-defendant pairs between 1990 and 2015 from USPTO. I focus on utility patents (level 830 patent), a type 1 infringement complaint comprising around 80% of all cases. I include plaintiff-defendant pairs that do not have counter filing cases in order to remove potential noise in the analysis.

Table 2: Sample overview

	Mean	St Dev.	Min	Median	Max	N
			Panel A: Plaintiffs - Controls			
Plaintiffs						
Assets	7.32	2.54	0.74	7.47	13.59	13312
Sales	6.89	2.61	0.00	6.97	12.04	13312
R&D	4.83	2.33	0.00	4.80	9.41	12915
Total Citations	5.68	2.24	0.69	5.87	11.25	12788
Total Patents	9.41	2.15	4.62	9.58	15.12	12788
Controls						
Assets	7.27	2.62	0.42	7.47	13.59	30714
Sales	6.86	2.70	0.00	7.00	12.04	30714
R&D	4.76	2.38	0.00	4.74	9.41	29603
Total Citations	5.27	2.40	0.69	5.58	9.68	28429
Total Patents	8.96	2.27	4.62	9.24	12.82	28429
			Panel B: Defendants - Controls			
Defendants						
Assets	7.44	2.33	0.10	7.55	13.45	12293
Sales	7.09	2.43	0.00	7.23	12.84	12293
R&D	4.85	2.13	0.00	4.74	9.44	11912
Total Citations	5.43	2.54	0.69	5.54	11.25	11214
Total Patents	9.21	2.45	4.62	9.21	15.12	11214
Controls						
Assets	7.37	2.40	0.10	7.52	13.45	31050
Sales	7.05	2.49	0.00	7.23	12.84	31050
R&D	4.64	2.27	0.00	4.52	9.44	29606
Total Citations	4.67	2.44	0.69	4.67	9.68	27238
Total Patents	8.48	2.38	4.62	8.41	12.82	27238

Note: This table presents summary statistics about litigation pairs for the main control group of the paper. Panel A consists of the plaintiff-defendant pairs that form a treatment group, and control-defendant pairs where controls are matched to plaintiffs. Panel B consists of the defendant-plaintiff pairs that form a treatment group, and control-plaintiff pairs where controls are matched to defendants. All the values are expressed in log term. Average values of preceding three years before litigation are used.

6 Main Results

The main analysis is composed of four parts. In Section 5. 1, I show who becomes plaintiffs or defendants. Then I identify the impact of litigation on both plaintiffs and defendants in Section 5.2. In Section 5.3, I show that litigants switch their innovation patterns and in Section 5.4, I show the results of the robustness test. The impact on the overall economy will be discussed in Section 6.

6.1 Ex ante analysis: Who are plaintiffs and defendants

I first show ex ante analysis results on who becomes litigants. Table 3 presents coefficient estimates from the conditional logit regression specified in equation 3. For columns (1)-(3), the dependent variable equals 1 for plaintiff-defendant pairs that form the treatment group, and 0 for the plaintiff-matched control pairs. For columns (4)-(6), the dependent variable equals 1 for plaintiff-defendant pairs, and 0 for the defendant-matched control pairs.

Columns (1) and (4) provide the basic results based on the use of complementary assets. If the patent portfolio distribution of two firms are closely related in a technology space, as proxied with *Technology Proximity*, they are more likely to be engaged in litigation. In addition, all *Patent Overlap* measures are also positive and significant. It means that if a plaintiff shares more external knowledge with the defendant, proxied by the number of *External Overlap*, then that firm is more eager to react by filing a litigation. More importantly, the coefficient of *Cross Overlap* measures is the largest and most significant at the 1% level in all cases. The coefficients on *Cross Overlap* and *External Overlap* tell us that two firms are grounded on overlapping external technologies as well as each other' technologies. These measures can be seen as direct measures indicating spillovers.

Columns (2)-(3) and (5)-(6) show the results with financial and innovation characteristics. Firstly, firm size matters for both firms at 1% significance level in columns (3) and (6). It suggests that larger firms can afford the cost of trial. In addition, firms that invest more in R&D become targets, which implies that firms place value on their innovation. Considering that innovation is a cumulative process, firms would be willing to secure exclusive rights as an innovator, thereby increasing the probability of litigation. Similarly, if a firm's intangible assets, as proxied with Tobin Q, are highly valued in the market with 1% significance level, it is more sensitive to any infringement as it attempts to keep its property rights. In summary, this finding is consistent with the literature that identify the characteristics of patent litigants. Moreover, this finding adds new evidence that relative characteristics also contribute to litigation: the intensive use of complementarity assets increases the probability of having litigation. Complementarity can explain 47% of results.

Table 3: Who are plaintiffs and defendants

	Panel A: Plaintiffs			Panel B: Defendants		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable : Litigation=1						
Technology Proximity	0.055***	0.051***	0.050***	0.064***	0.055***	0.054***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
External overlap	1.578***	1.273***	1.056***	0.360**	0.290**	0.325**
	(0.386)	(0.341)	(0.385)	(0.141)	(0.147)	(0.154)
Cross overlap	18.257***	8.960*	13.042**	1.313***	1.495***	1.611***
	(5.007)	(5.088)	(5.793)	(0.484)	(0.533)	(0.477)
Self overlap	0.191***	0.067	0.142***	0.017	-0.033	0.017
	(0.036)	(0.043)	(0.040)	(0.035)	(0.050)	(0.049)
Asset		0.091**	0.143***		0.316***	0.246***
		(0.040)	(0.044)		(0.041)	(0.045)
TobinQ		0.654***	0.668***		0.610***	0.566***
		(0.129)	(0.125)		(0.128)	(0.126)
Total Patents		0.652***			0.397***	
		(0.053)			(0.042)	
R&D			0.422***			0.448***
			(0.048)			(0.050)
Observations	3,364	2,932	2,891	3,225	2,775	2,746
Pseudo R2	0.471	0.723	0.663	0.471	0.678	0.675
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1						

Note: This table reports the coefficient estimates from the conditional logit model in equation 3. For columns (1)-(3), the dependent variable equals one for the plaintiff-defendant pairs that form the treatment group, and zero for the plaintiff-matched control pairs. For columns (4)-(6), the dependent variable equals one for the plaintiff-defendant pairs, and zero for the defendant-matched control pairs. For independent variables, three-year average values before litigation year are used. Standard errors are clustered at case-pair levels and are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Overall, these results provide strong evidence that spillovers are important elements in determining litigation cases when two firms are closely located in the technology space. At the same time, the results can indicate that there exists conflicts of interest triggering litigation.

6.2 Ex post analysis: The impact of litigation on litigants

6.2.1 *Technology Proximity*

Table 4 presents results for difference-in-difference in equation 4. Dependent variables are two *Technology Proximity* measures constructed in Section 3.1 1) between plaintiffs and litigants and 2) between a plaintiff (or a defendant) and a technology class under patent litigation (LP). Columns (1) and (3) provide estimate results of plaintiffs-defendants

Table 4: The impact of litigation on *Technology Proximity*

	Panel A: Plaintiffs		Panel B: Defendants	
	(1)	(2)	(3)	(4)
	$Proximity_{P,D}$	$Proximity_{P,LP}$	$Proximity_{D,P}$	$Proximity_{D,LP}$
Treat x Post litigation	-0.062***	-0.030***	-0.057***	-0.007
	(0.006)	(0.006)	(0.006)	(0.008)
Observations	45,339	16,152	46,136	15,870
R-squared	0.749	0.894	0.745	0.861
Year FE	✓	✓	✓	✓
Case FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: This table reports coefficient results from difference-in-difference regression in equation 4. The dependant variable is *Technology Proximity* measured in the [-5, 5] year window around the litigation year. Post-litigation equals one after and including litigation year. The standard error is clustered at case-level across all analyses. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Technology Proximity. As plaintiffs and defendants have their own case level control groups, the results are provided using two different samples, respectively. The results in columns (1) and (3) show that litigation leads to a reduction in *Technology Proximity* indexes by 0.06 and 0.057, respectively. As the results are proven in two different samples, the results are confirmed two times by using different samples. Relative distance between two litigants is reduced compared to after litigation. This suggests movement of relative location change in litigants' portfolios.

On the other hand, columns (2) and (4) indicate *Technology Proximity* measures between the LP and each litigant. Since LP is fixed at one point in the technology classification across the years, the coefficients provide more information on who moves from this fixed point. Interestingly the proximity decreases for plaintiffs by 0.03, while it does not show any significant variation for defendants. This feature will be discussed in the following Section.

All difference-in-difference analysis includes firm fixed effect, year fixed effect and case fixed effect. The firm fixed effects ensure that I compare the impact of litigation within the same firm. Therefore, the estimates are not affected by any firm-specific time invariant characteristics, such as a firm's propensity for patents, R&D intensity, and so on.

6.2.2 Patent Citation Overlap

Table 5 reports coefficient estimates from difference-in-difference results in equation 4. For dependent variables, three *Patent Overlap* measures constructed in Section 3.2 are used. Columns (1) and (4) show that a firm's external technology overlap index is decreased by 0.22 and 039 respectively, for both plaintiffs and defendants after litigation. The *External Overlap* variable provides information about the external knowledge base both firms use in their innovation. The coefficients are statistically significant at 1% level and greatest among all citation proximity measures, implying both firms are actively engaged in the use of external knowledge. As a firm creates innovation based on previous inventions described as creative destruction (Aghion and Howitt 1992), the active use of patents from third parties implies that spillover effects are not limited to just the plaintiffs-defendants relationship but linked with many other firms, like a complex knowledge web. Therefore, the results suggest that spillovers reduction involves other parties than only the litigants. On the other hand, *Cross Overlap* provides us with the degree of complementarity between pairs of firms. These results provide the most accurate measure of spillovers in a narrow sense: whether plaintiffs and defendants are closely related and share technologies with each other. As expected, the results show negative and highly significant coefficients at 1% level as shown in column (2) and (4). It indicates that patents of both firms reduce the use of knowledge assets from the opponent. It is noticeable that a reduction is greater for defendants, 0.13 in magnitude compared to 0.08 for plaintiffs, and coefficients are highly significant at 1% level. It reveals the direction of spillovers, that is, that defendants use plaintiffs' knowledge assets more than the plaintiffs use defendants' knowledge. Lastly, *Self Overlap* indicates whether firms use their own technologies. Often, this is the case when firms deepen their ongoing innovation, thereby adding more complexity to the previous findings. Defendants do not show any specific changes; however, it is noticeable that plaintiff firms use less of their previous findings. The results are coherent with previous results using *Technology Proximity* measures. These two measures uniformly suggest that plaintiffs are departing from litigation related technology.

Overall, these two different analyses confirm that, after litigation, complementarity between plaintiffs and defendants diminishes suggesting the reduction of spillovers among litigants. At the same time, the results also imply that litigation between two parties in-

Table 5: Patent Citation Proximity

	Panel A: Plaintiffs			Panel B: Defendants		
	(1)	(2)	(3)	(4)	(5)	(6)
	External	Cross	Self	External	Cross	Self
Treat x Post litigation	-0.228*** (0.068)	-0.088*** (0.018)	-0.165*** (0.030)	-0.399*** (0.068)	-0.134*** (0.018)	0.084** (0.035)
Observations	8,367	25,741	27,827	8,650	20,633	22,756
R-squared	0.860	0.721	0.620	0.840	0.733	0.622
Year FE	✓	✓	✓	✓	✓	✓
Case FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1						

Note: This table reports coefficient results from difference-in-difference regression. Panel A consists of the plaintiff-defendant pairs that form a treatment group, and plaintiff-matched control pairs. Panel B consist of the plaintiff-defendant pairs that form a treatment group, and defendant-matched control pairs. The dependant variable is *Patent Overlap* measures constructed in Section 3.2: External Overlap, *Cross Overlap* and *Self Overlap* in the [-5, 5] year window around the litigation year. Post-litigation equals one after and including litigation year. Treat equals one when the pair is plaintiff-defendant match, and zero for controls. Total number of patent application is included as a control. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1

cludes knowledge diffusion, even among third parties.

6.3 Ex post analysis: Change of technology strategy

The previous sections focus on litigation over spillovers and find that the complementary relationship among litigants is weakened. In addition, I find that plaintiffs move away from the technology under litigation. In this section, I examine the direction and magnitude of those changes by constructing new measures.

Firms can increase the intensity of their innovation and/or broaden their technology areas. Having a larger patent portfolio can put a firm in a better position. For example, firms conduct strategic patenting to gain bargaining power and an ability to operate freely in a patent dispute (Noel and Schankerman 2013). Ziedonis (2004) finds that firms patent more aggressively when they observe greater fragmentation in the patenting behavior of rival firms. The incentive towards strategic patenting might be larger for firms under litigation since a portfolio size and technology concentration significantly affect litigation risk (Lanjouw and Schankerman 2004), which can explain the results of this paper.

In this regard, I construct two measures to examine the degree of portfolio diversity and concentration.

Patent Index (PI)

I construct the *Patent Index (PI)* patenting activity in narrowly defined technology classification to explore the magnitude of patenting behaviors. The calculation is shown as below:

$$\text{Patent Index}_{C_p,i,t} = \sum_{C_p=1}^{N} \frac{Nb\,of\,patents_{C_p,i,t}}{mean(Nb\,of\,patents_{C_p,t})}$$

where $p \in \{LP, -LP\}$ and C_p ranges from 1 to N technology subclasses, c denotes technology class, and t denotes year. *LP* and *-LP* denote litigation related technology sectors and non-litigation related sectors, respectively. This index measures total number of patents in each technology category, scaled by the mean number of patents within an industry. This measurement allows for the comparison of numbers of patents in firms' portfolio across different technology classes, in terms of complexity and width.

I distinguish two technology classifications: PI_{LP} with technologies related to litigation and PI_{-LP} in non-litigation technology classes. I use detailed technology classification at 667 levels, which is the most narrowly defined classification in the Coordinated Patent Classification (CPC)[4].

Concentration Index (CI)

I construct the Concentration Index using the Herfindahl-Hirschman Index (HHI) method to examine the concentration of patenting activities in each technology category. The index is calculated by squaring the share of patents in each patent class, then summed up to one index. The calculation is shown as below:

$$\mathrm{CI}_{C_p,i,c,t} = \sum_{c=1}^{N} \mathrm{S}^2_{i,c,t}$$

where $S_{i,c,t}$ is the share of patents in class c to total number of technologies of firm at time t. This index equals one when a firm concentrates in a single sector.

Table 6 provides coefficient estimates for two indexes based on equation (2). Dependent variables are PI and CI for LP technology and non-LP technology. For LP technology sec-

4. CPC is the Cooperative Patent Classification scheme used by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO). It is much more detailed than International patent classification. CPC classification codes can be used to carry out searches of both European and USPTO Classification databases. (*International Patent Classification: Frequently Asked Questions* 2020)

tor, after litigation, PI decreases for plaintiffs and defendants as in Columns (1) and (3). A decrease of PI in LP sectors means that both plaintiffs and defendants reduce innovation in LP sector. Litigation reduces the scale of innovation in the litigation-related sector, demonstrating the scale effect. The reasons can be diverse; but in line with previous literature, firms take defensive patenting strategies (Hargreaves 2011) to avoid further litigation and guarantee freedom of operation. In addition, firms may create patent thicket (Hall and Harhoff 2012). Also, the plaintiff firm's concentration decreases as shown in column (2), suggesting innovation activities become allocated into broader levels than before. This suggests that firms substitute innovation investment with other possible strategic assets; therefore, firms pursue more expansive, strategic patenting. As for the *Non-LP* sector, defendants show substitution effects, suggesting firms would move to litigation-free technologies.

6.4 Robustness

This section examines the robustness of the main results in section 6.1 and section 6.2. Firstly, I examine dynamic effects of litigation and, secondly, I test a placebo impact using different litigation timing.

6.4.1 Dynamic effects on the use of complementarity knowledge

One endogeneity concern is about the timing of litigation. Although firms that move in a strategic way were removed from the sample and such characteristics are controlled by several fixed effects, one may be concerned about endogeneity.

In this section, I examine the existence of reverse causality by tracing dynamic effects. If a plaintiff intends to shift its technology portfolio before litigation, then one can predict that Technology Proximity measures and *Patent Overlap* measures begin to change even in years before the litigation year.

Tables 7 and 8 provides coefficient estimates for a set of dummy variables for corresponding years. The year dummy *(t-i)* equals 1 if year is i years before the litigation year t, or 0 otherwise. Year t is excluded due to multicollinearity issues. Columns (1)-(2) present specifications using *Technology Proximity* measures and columns (3)-(5) present results using *Patent Overlap* measures for plaintiffs and defendants respectively. The results show that the coefficients on the dummies for years after the litigation turn to negative, while dummies before the litigation are positive. This result confirms not only the robustness of the results in previous sections but also shows the impact and direction of spillovers. The use of complementary assets intensifies until the litigation, then decreases after litigation, which confirms that increased spillovers create a litigation event and then lessen as a result of litigation. Given that *Patent Overlap* measures are based on year of patent application and not year of patent granted, the results suggest rapid reactions to innovation

Table 6: Intensity and magnitude of Innovation after litigation

	LP technology sector			
	Panel A: Plaintiffs		Panel B: Defendants	
	(1)	(2)	(3)	(4)
	PI_{LP}	CI_{LP}	PI_{LP}	CI_{LP}
Treat x Post litigation	-0.050***	-0.014*	-0.026*	0.014
	(0.012)	(0.008)	(0.014)	(0.017)
Observations	45,339	45,339	46,136	46,136
R-squared	0.557	0.309	0.306	0.356
Year FE	✓	✓	✓	✓
Case FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
	Non-LP technology sector			
	Panel A: Plaintiffs		Panel B: Defendants	
	(5)	(6)	(7)	(8)
	PI_{-LP}	CI_{-LP}	PI_{-LP}	CI_{-LP}
Treat x Post litigation	-0.073	-0.012	0.491***	-0.062**
	(0.130)	(0.010)	(0.181)	(0.026)
Observations	17,096	25,886	17,239	25,142
R-squared	0.910	0.448	0.873	0.523
Year FE	✓	✓	✓	✓
Case FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Note: This table reports coefficient results from difference-in-difference regression in equation (2). Panel A shows results for plaintiffs and Panel B shows results for defendants. The dependant variable is Patent Index (PI), the sum of the number of patents in each technology class scaled by the average number of patent shares in the same technology class. The Concentration Index (CI) is calculated as a sum of squares of patent shares in each technology class. Number of patents is included as a control. *Treat* equals one when the pair is plaintiff-defendant match, and zero for controls. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

activities around litigation.

Table 7: Dynamic effects on complementary knowledge - Plaintiff

	Panel A: Plaintiffs				
	(1)	(2)	(3)	(4)	(5)
	$Proximity_{P,D}$	$Proximity_{P,LP}$	External	Cross	Self
t-5 year x treated	0.021***	0.007	0.351**	0.103***	-0.011
	(0.008)	(0.010)	(0.149)	(0.032)	(0.046)
t-4 year x treated	0.027***	0.003	0.351***	0.113***	-0.045
	(0.007)	(0.010)	(0.124)	(0.028)	(0.042)
t-3 year x treated	0.021***	0.010	0.305***	0.080***	-0.030
	(0.006)	(0.007)	(0.097)	(0.024)	(0.036)
t-2 year x treated	0.015***	0.001	0.236***	0.084***	-0.029
	(0.006)	(0.006)	(0.079)	(0.022)	(0.030)
t-1 year x treated	0.014**	-0.003	0.137**	0.024	-0.051*
	(0.006)	(0.006)	(0.059)	(0.019)	(0.027)
t+1 year x treated	-0.003	-0.022***	-0.052	-0.009	0.005
	(0.006)	(0.007)	(0.066)	(0.021)	(0.024)
t+2 year x treated	-0.023***	-0.023***	-0.221***	-0.026	-0.002
	(0.007)	(0.006)	(0.083)	(0.023)	(0.027)
t+3 year x treated	-0.044***	-0.021***	-0.382***	-0.083***	-0.008
	(0.007)	(0.007)	(0.105)	(0.026)	(0.031)
t+4 year x treated	-0.053***	-0.039***	-0.553***	-0.087***	-0.025
	(0.008)	(0.009)	(0.136)	(0.031)	(0.036)
t+5 year x treated	-0.073***	-0.035***	-0.602***	-0.110***	-0.051
	(0.009)	(0.009)	(0.159)	(0.034)	(0.041)
Observations	45,681	16,311	5,636	14,520	16,893
R-squared	0.756	0.893	0.875	0.687	0.652
Year FE	✓	✓	✓	✓	✓
Case FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Note: This table reports the dynamics of litigation results for dependant variables: 1) *Technology Proximity* in columns (1)-(2); and 2) Patent Overlap in columns (3)-(5). The variable *t-i* year is a dummy variable equal to one if the observation is from *i* year preceding the litigation. *Treat* equals one when a firm is part of a plaintiff-defendant pair in panel B, otherwise is zero. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

6.4.2 Placebo test

I conduct an additional placebo test in order to check whether the results are driven by confounding factors at the time of litigation.

Table 8: Dynamic effects on complementary knowledge - Defendant

	Panel B: Defendants				
	(1)	(2)	(3)	(4)	(5)
	$Proximity_{P,D}$	$Proximity_{P,LP}$	External	Cross	Self
t-5 year x treated	2.659***	1.739	0.265*	0.097***	-0.198***
	(0.892)	(1.251)	(0.148)	(0.036)	(0.068)
t-4 year x treated	3.019***	1.652	0.221*	0.109***	-0.145**
	(0.789)	(1.102)	(0.124)	(0.029)	(0.060)
t-3 year x treated	3.043***	1.766**	0.182*	0.058**	-0.107**
	(0.721)	(0.899)	(0.099)	(0.026)	(0.051)
t-2 year x treated	1.661***	1.432	0.178**	0.021	-0.075*
	(0.596)	(0.876)	(0.079)	(0.024)	(0.043)
t-1 year x treated	1.565***	2.031***	0.069	0.028	0.003
	(0.604)	(0.769)	(0.061)	(0.018)	(0.036)
t+1 year x treated	0.544	1.145	-0.067	-0.007	0.053*
	(0.610)	(0.726)	(0.068)	(0.023)	(0.031)
t+2 year x treated	-1.852**	1.773**	-0.224**	-0.024	0.087***
	(0.733)	(0.780)	(0.087)	(0.025)	(0.033)
t+3 year x treated	-4.354***	-0.472	-0.346***	-0.056*	0.081**
	(0.824)	(0.913)	(0.108)	(0.029)	(0.039)
t+4 year x treated	-5.316***	0.311	-0.472***	-0.044	0.123***
	(0.902)	(0.969)	(0.129)	(0.031)	(0.044)
t+5 year x treated	-6.752***	0.354	-0.533***	-0.101***	0.108**
	(1.005)	(1.155)	(0.159)	(0.037)	(0.049)
Observations	46,078	15,954	5,494	12,396	14,727
R-squared	0.749	0.860	0.858	0.678	0.635
Year FE	✓	✓	✓	✓	✓
Case FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Note: This table reports the dynamics of litigation results for dependant variables: 1) *Technology Proximity* in columns (1)-(2); and 2) Patent Overlap in columns (3)-(5). The variable *t-i* year is a dummy variable equal to one if the observation is from *i* year preceding the litigation. *Treat* equals one when a firm is part of a plaintiff-defendant pair in panel B, otherwise is zero. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

When I impose a different point of time for the litigation event, the results fail to find the same reaction. I assume that litigation occurs at *t-5* instead of *t* and drop observations after litigation. The results show that the resulting coefficients are insignificant across years. Again, it confirms that there is no pre-trend driving change in the use of complementary asset or firm strategies. The results are presented in table 9.

6.4.3 Other control groups

In addition, I use three difference control samples to examine the results. All the main results are reproduced when using two other samples. The results are presented in the Appendix.

Table 9: Placebo test - *Technology Proximity* and *Patent Overlap*

	Panel A: Plaintiffs				Panel B: Defendants			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Proximity_{P,D}$	$Proximity_{P,LP}$	External	Cross	$Proximity_{D,P}$	$Proximity_{D,LP}$	External	Cross
Treat x Post litigation	-0.651	-0.422	-0.091	-0.028	-0.934	0.435	-0.042	-0.014
	(0.597)	(0.859)	(0.091)	(0.023)	(0.670)	(1.138)	(0.095)	(0.024)
Observations	20,812	7,682	4,509	11,001	20,596	7,121	4,654	8,616
R-squared	0.791	0.879	0.886	0.826	0.789	0.830	0.871	0.843
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Case FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: This table reports coefficient results from difference-in-difference regression of the placebo test that impose litigation year at t-5 instead of t. Panel A is the results for plaintiffs and Panel B is the results for defendants. The dependant variables are the *Technology Proximity Patent Citation* measures in the [-5, 5] year window around the litigation year. Post-litigation equals one after and including litigation year. *Treat* equals one when the pair is plaintiff-defendant match, and zero for controls. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

7 Further analysis: Impact on overall economy

In previous sections, I examine the impact of litigation on plaintiffs and defendants in terms of their relative relationship based on micro-level evidence. In this part, I examine the impact of litigation using a macro-level approach. As suggested in previous sections, all firms are closely connected through knowledge sharing and there exists a high degree of citing activities. In this regard, if knowledge spillovers occur from the frontier to the imitators (Jovanovic and Macdonald 1994), diffusion arises serially from the top of innovation to the bottom by many firms' activities including litigants. Previous literature supports the importance of the role between knowledge providers and other firms (Cirera and Maloney 2017), and the role of middlemen in overcoming diffusion asymmetry. Therefore, the potential impact of litigants located in the upstream of knowledge diffusion, such as innovators and intermediaries of knowledge diffusion, would be large on the overall economy. Therefore, it is highly relevant to examine the economic impact of knowledge diffusion. In particular, litigation can be one of the reasons for the slowing down of knowledge diffusion, which is then linked to productivity slowdown.

In this part, I firstly examine the impact on a firm's innovation and financial condition. Secondly, I examine the litigation impact on the plaintiff-defendant-frontier relationship to find its link with the overall economy.

7.1 Innovation

Table 10 presents coefficient results on firms' innovation activity. In Section 6.3, the effect shows that litigants reduce innovation, proxied by *Patent Index* in LP sector, while defendants increase patenting in non-LP sectors. The increase in R&D could explain defendants' exploratory patenting activity, in line with an increase in CI_{-LP}. More importantly, the number of citations and the number of cited patents are reduced, as shown in columns (2), (3), and columns (5), (6). Plaintiffs reduce the number of prior patent citations by 18%, suggesting that new patenting activity slows down; as shown in column (3), a decrease in the number of patents by 0.11. Similarly, defendants reduce the number of citations by 13%. Spillovers can be measured using the *citing action* of prior works and the *cited action* from others (Jaffe et al. 2000). Therefore, a decrease in both citing and being cited in innovation activities means that the role of litigants as intermediaries is contracted and reduced, further signaling a decline in promoting knowledge diffusion.

7.2 Financial condition

Table 11 presents the coefficient results on a firm's financial condition. As shown in columns (1) and (6), the productivity level of plaintiffs is little affected and shows an increase by

5. I follow the estimation strategy of Baqaee and Farhi (n.d.) using the variable construction of de Loecker

Table 10: Innovation

	Panel A: Plaintiffs				Panel B: Defendants				
	(1)	(2)	(3)		(4)	(5)	(6)		
	R&D	# citation	# cited		R&D	# citation	# cited		
Treat x Post litigation	-0.012	-0.189***	-0.435***		0.112***	-0.137***	-0.317***		
	(0.025)	(0.029)	(0.040)		(0.030)	(1.523)	(0.039)		
Observations	14,765	29,005	36,572		13,772	26,115	34,200		
R-squared	0.974	0.916	0.895		0.943	0.972	0.896		
Year FE	✓	✓	✓	✓		✓	✓	✓	✓
Case FE	✓	✓	✓	✓		✓	✓	✓	✓
Firm FE	✓	✓	✓	✓		✓	✓	✓	✓

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: This table reports coefficient results from difference-in-difference regression. Panel A consists of the plaintiff-defendant pairs that form a treatment group, and control-defendant pairs where controls are matched to plaintiffs. Panel B consists of defendant-plaintiff pairs that form a treatment group, and control-plaintiff pairs where controls are matched to defendant. The dependant variable is innovation measure in the [-5, 5] year window around the litigation year. Post-litigation equals one after and including litigation year. Treat equals one when the pair is plaintiff-defendant match, and zero for controls. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

3%; however, the impact on defendants is the opposite.[5] In addition, Tobin Q decreases by 2% for plaintiffs and 3% for defendants. The importance of a firm's intangible assets is associated with the frequency of citations of a firm's innovation (A. Hall et al. 2005). Therefore, a decreases in citations can explain a decrease in the value of a firm's intangible assets, proxied by Tobin Q. Moreover, litigation risk further damages a firm's values. While the causality driven by litigation a firm's financial condition is not covered in this paper, I show that litigation impacts a firm's financial condition, particularly its productivity and firm values.

7.3 Distance to the frontier : *Technology Proximity* and *Patent Overlap*

In order to survive at the frontier, firms must continue to innovate. Therefore, if litigants reduce their own innovation as well as spillovers from rival firms at the frontier, they will fall behind the frontier. Therefore, to understand the impact of litigation on the overall economy, I examine the use of complementarity assets in the plaintiffs-defendants-frontier relationship. I conduct the main analysis using litigants' position relative to the frontier. The definition of a frontier firms is a firm who is at the top in total number of citations in each technology class for the last five years before litigation and who are not engaged in litigation during that 5-year period. For the analysis of total factor productivity (TFP), I also define a firm in TFP who is the most productive firm in each technology class in each year. I assume that the frontier firms continue to invest in the same technology sector.

This analysis also answers a concern about measurement error. As *Technology Proximity* measures are examined as a relative relation, one can raise the concern that a plaintiff and a defendant may move together in technology space but with a different degree of magnitude. Due to the confounding effects, econometricians would understand only that proximity is decreased. Using *Technology Proximity*$_{p(d),LP}$ in Section 6.2, I already show the direction of moves among technology classes. The comparison using plaintiff-frontier and defendant-frontier relation allows one to understand the changes vertically compared to the frontier. This confirms that there occurs a decline, from an objective point of view.

7.3.1 *Technology Proximity* with the frontier

Table 12 shows that the decrease in proximity of litigant firms' patent portfolios to the frontier decreases for both plaintiffs and defendants. On the other hand, Proximity measures between the frontier and LP do not indicate any significant results. Therefore, it is reasonable to assume that frontier firms do not experience any change in their ongoing innovation. On the other hand, *Technology proximity* coefficients strongly indicate that, after litigation, litigants' technology portfolio becomes distant from the frontier.

Eeckhout (2017) in Compustat.

Table 11: Financial condition

	Panel A: Plaintiffs				Panel B: Defendants			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tfp	tobinQ	asset	leverage	Tfp	tobinQ	asset	leverage
Treat x Post litigation	0.030***	-0.021***	0.004	0.153	-0.024	-0.033***	0.061***	-0.806
	(0.007)	(0.006)	(0.010)	(0.122)	(0.007)	(0.007)	(0.010)	(1.101)
Observations	34,993	39,144	40,563	40,407	34,146	38,089	39,570	39,455
R-squared	0.791	0.677	0.969	0.119	0.928	0.686	0.967	0.127
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Case FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: This table reports coefficient results from difference-in-difference regression. Panel A consists of the plaintiff-defendant pairs that form a treatment group, and control-defendant pairs where controls are matched to plaintiffs. Panel B consists of defendant-plaintiff pairs that form a treatment group, and control-plaintiff pairs where controls are matched to defendant. The dependant variable is innovation measure in the [-5, 5] year window around the litigation year. Post-litigation equals one after and including litigation year. Treat equals one when the pair is plaintiff-defendant match, and zero for controls. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10

Table 12: *Technology Proximity* with the frontier

	Panel A: Plaintiffs	Panel B: Defendants
	(1)	(2)
Frontier	$Proximity_{F,P}$	$Proximity_{F,D}$
Treat x Post litigation	-1.642***	-2.286***
	(0.448)	(0.433)
Observations	45,446	46,739
R-squared	0.770	0.750
Year FE	✓	✓
Case FE	✓	✓
Firm FE	✓	✓
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

Note: This table reports coefficient results from difference-in-difference regression in equation 4. Panel A shows results for the plaintiff-defendant and plaintiff-matched sample and Panel B shows results for plaintiff-defendant and defendant-matched sample. The dependant variable is *Technology Proximity* measures: *Technology Proximity*$_{F,P}$ and *Technology Proximity*$_{F,D}$. The regression is conducted in the [-5, 5] year window around the litigation year. Post-litigation equals one after and including litigation year. Treat equals one when the pair is the plaintiff-defendant match, and zero for controls. Total number of patent applications is included as a control. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

7.3.2 *Patent Overlap* with the frontier

Table 13 presents coefficient results for *Patent Overlap* measures. As expected, the *Cross Overlap* measure is decreased for both litigants, confirming previous results. Both *External Overlap* and *Cross Overlap* coefficients strongly indicate that, after litigation, litigants reduce the use of internal and external knowledge assets. Recall that spillovers occurs when firms cite each other's knowledge assets. Thus, the decrease in complementarity between plaintiffs and the frontier as well as between defendants and the frontier implies that the spillovers from the frontier to litigants decrease.

7.3.3 Gap in productivity growth between the frontier and litigants

In the aggregated economy, the frontier produces constant productivity growth. At the same time, however, the rising productivity gap between the frontier and other firms raises concerns about this divergence. This concern is exactly repeated within the plaintiffs-defendants-frontier relationships. The slowdown in productivity growth convergence im-

Table 13: *Patent Overlap* between the frontier and the litigants

	Panel A: Plaintiffs		Panel B: Defendants	
	(1)	(2)	(3)	(4)
	External	Cross	External	Cross
Treat x Post litigation	-0.167	-0.092***	-0.219*	-0.111***
	(0.111)	(0.030)	(0.113)	(0.030)
Observations	6,312	14,823	5,948	12,655
R-squared	0.856	0.676	0.859	0.679
Year FE	✓	✓	✓	✓
Case FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Note: This table reports coefficient results from difference-in-difference regression in equation 4. Panel A consists of plaintiff-defendant pairs that form a treatment group, and control-defendant pairs where controls are matched to plaintiffs. Panel B consists of defendant-plaintiff pairs that form a treatment group, and control-plaintiff pairs where controls are matched to defendants. The dependant variable is the patent citation measures: *External Overlap*, *Cross Overlap* and *Self Overlap*. The regression is conducted in the [-5, 5] year window around the litigation year. Post-litigation equals one after and including litigation year. *Treat* equals one when the pair is plaintiff-defendant match, and zero for controls. Total number of patent applications is included as a control. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

plies that technologies do not immediately diffuse to other firms in the economy (Andrews et al. 2016). I try to find the answer from global productivity divergence.

To examine this causality, I first examine the relation among plaintiffs-defendants-frontier pairs. As shown in Table 14, the gap in productivity growth between the frontier and defendants increases about 2.2% and the coefficients are highly significant at 1% level. For plaintiffs, the gap rises by 1.3%. Although it is shown that plaintiffs increase productivity by 3% in the previous section, the results suggest that the productivity growth of plaintiffs is not enough fast to catch up to the productivity of the frontier. As a result, plaintiffs' productivity growth slows, resulting in an increasing gap with the frontier in terms of productivity.

In summary, this result implies that the productivity growth rates of both litigants are slower than that of frontier firms. Therefore, litigants fall behind of the frontier, the ri-

Table 14: Gap in Productivity (TFP) growth rates between the frontier and litigants

	Frontier in # patent		Frontier in productivity	
	(1)	(2)	(3)	(4)
	$Gap_{F,P}$	$Gap_{F,D}$	$Gap_{F,P}$	$Gap_{F,D}$
Treat x Post litigation	0.005	0.023***	0.013**	0.022***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	29,228	28,749	30,013	28,736
R-squared	0.555	0.552	0.556	0.552
Year FE	✓	✓	✓	✓
Case FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Note: This table reports coefficient results from difference-in-difference regression. The dependant variable is the gap in productivity growth rates. Columns (1), (2) report the results of analysis using the frontier firm that receives the largest number of citation. Columns (3), (4) report the results of analysis using the frontier firm that exhibits the highest TFP growth. Columns (1) and (3) report the result between the frontier (F) and plaintiffs(p); and columns (2) and (4) report the results between the frontier(f) and plaintiffs(d). Post-litigation equals 1 after and including litigation year. *Treat* equals 1 when the pair is a plaintiff-defendant match, and 0 for controls. Standard errors are clustered at the case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

vals in technology innovation converge with each other, while their gap from the frontier increases. By using *External Overlap*, *Cross Overlap*, and *Self Overlap*, I show that spillovers happen serially among firms. The results show that the diffusion of knowledge at the frontier level diminishes. Furthermore, given that the knowledge diffusion occurs through firms that link the frontier with the laggards, the impact is not limited to just the litigants. In summary, this finding suggests that there is less technology diffusion among these firms. Considering that plaintiffs and defendants are active innovators and located in the very right tails of the firm distribution, attention must be paid to monitor how the IPRs enforcement system can promote knowledge diffusion.

8 Conclusion

In this paper, I investigate the impact of patent litigation by focusing on complementary assets between plaintiffs and defendants. Using a novel plaintiffs-defendants-case pair data set covering litigation among practicing entities in the United States, I find that the proximity of two firms in a technology space decreases throughout litigation, and firms switch technology strategies. The following are particular findings of this paper:

In the first section, I first show that when litigants are innovators at the frontier and share complementary knowledge assets, that situation eventually could trigger patent litigation. Firms that are closely located in a technology space actively share external and internal knowledge, but their proximity to each other diminishes after litigation. Further, I find that litigation results in the scale effect, which reduces follow-on innovation, and the substitution effect, in which firms diversify their patent applications to sectors other than the litigation sector. This suggests that firms make defensive patenting decisions.

In the second section, I present how litigation results can explain the slowdown of business dynamism in the United States. Litigants become distant from the technology frontier, and firms reduce their innovative activities. In addition, litigating firms fail to catch up to the growth of the frontier firm. As a result, these firms decrease their role linking upstream knowledge diffusion with the overall economy.

The findings of this paper have several important implications. They confirm the role of complementary assets in creating knowledge spillovers and the damage that litigation produces on such spillovers. More importantly, this paper provides one possible explanation of productivity slowdown by offering evidence of a decline in knowledge diffusion. By examining patent litigation, I ask whether the Intellectual Property Rights (IPRs) enforcement systems meet its designed objective. Thus, this paper encourages policymakers to pay more attention to the negative impacts of patent litigation and how to improve the implementation of the system to meet its objective more positively.

Many further research projects can be developed. First, litigation impact can be examined according to firm and industry characteristics. Second, litigants' ex-post patenting behaviors can be examined, focusing on litigants' strategic move to acquire complementary assets. Litigants may search out other firms that possess technology similar to their opponents'.

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Appendix

A Placebo Test

A.1: Intensity and magnitude of patent

	LP technology sector			
	Panel A: Plaintiffs		Panel B: Defendants	
	(1)	(2)	(3)	(4)
	PI_{LP}	CI_{LP}	PI_{LP}	CI_{LP}
Treat x Post litigation	0.027	-0.018	0.025**	0.007
	(0.018)	(0.014)	(0.010)	(0.015)
Observations	20,812	20,812	20,596	20,596
R-squared	0.720	0.568	0.705	0.550
Year FE	✓	✓	✓	✓
Case FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
	Non-LP technology sector			
	Panel A: Plaintiffs		Panel B: Defendants	
	(5)	(6)	(7)	(8)
	PI_{-LP}	CI_{-LP}	PI_{-LP}	CI_{-LP}
Treat x Post litigation	20.002	-0.107***	0.237	0.055
	(51.110)	(0.033)	(0.183)	(0.036)
Observations	15,802	15,802	8,477	13,989
R-squared	0.751	0.693	0.883	0.707
Year FE	✓	✓	✓	✓
Case FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Note: This table reports coefficient results from difference-in-differences regressions. Panel A is the results for plaintiffs and Panel B is the results for defendants. The dependant variable is the Patent Index (PI), the sum of number of patents in each technology class scaled by the average number of patent shares in the same technology class. Concentration Index(CI) is calculated as a sum of patent shares in each technology class. The variable, number of patents is included as a control. *Treat* equals one when the pair is plaintiff-defendant match, and zero for controls. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

B Results in Control 2 & Control 3

A.2: *Technology Proximity* citation - Control group 2

	Panel A: Plaintiffs					Panel B: Defendants				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$Prox_{P,D}$	$Prox_{P,LP}$	External	Cross	Self	$Prox_{D,P}$	$Prox_{D,LP}$	External	Cross	Self
Treat x Post litigation	-6.699***	-4.212***	-0.185**	-0.099***	-0.088***	-5.913***	0.010	-0.233***	-0.055**	0.141***
	(0.595)	(0.655)	(0.092)	(0.022)	(0.031)	(0.616)	(0.835)	(0.081)	(0.023)	(0.037)
Observations	45,405	18,962	6,985	18,628	21,220	45,077	17,774	7,254	15,141	17,524
R-squared	0.725	0.832	0.866	0.698	0.661	0.729	0.816	0.844	0.709	0.662
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Case FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: This table reports coefficient results from difference-in-differences regressions. Panel A is the results for plaintiffs and Panel B is the results for defendants. The dependant variable is the *Technology Proximity* measure in the [-5, 5] year window around the litigation year. Post-litigation equals one after and including litigation year. *Treat* equals one when the pair is plaintiff-defendant match, and zero for controls. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

A.3: *Technology Proximity* citation - Control group 3

	Panel A: Plaintiffs					Panel B: Defendants				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$Prox_{P,D}$	$Prox_{P,LP}$	External	Cross	Self	$Prox_{D,P}$	$Prox_{D,LP}$	External	Cross	Self
Treat x Post litigation	-5.674***	-2.508***	-0.438***	-0.089***	0.049*	-5.455***	0.740	-0.586***	-0.066***	0.187***
	(0.587)	(0.635)	(0.096)	(0.021)	(0.028)	(0.597)	(0.803)	(0.088)	(0.022)	(0.033)
Observations	79,000	22,922	7,293	20,701	25,201	75,930	20,400	7,529	17,417	21,374
R-squared	0.647	0.820	0.853	0.650	0.606	0.658	0.790	0.814	0.663	0.606
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Case FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: This table reports coefficient results from difference-in-differences regressions. Panel A is the results for plaintiffs and Panel B is the results for defendants. The dependant variable is the Technology Proximity measure in the [-5, 5] year window around the litigation year. Post-litigation equals one after and including litigation year. *Treat* equals one when the pair is plaintiff-defendant match, and zero for controls. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

A.4: Intensity and magnitude of patent - Control group 2

	LP technology sector				Non-LP technology sector			
	Panel A: Plaintiffs		Panel B: Defendants		Panel A: Plaintiffs		Panel B: Defendants	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PI_{LP}	CI_{LP}	PI_{LP}	CI_{LP}	PI_{-LP}	CI_{-LP}	PI_{-LP}	CI_{-LP}
Treat x Post litigation	-0.064***	-0.055**	0.112***	-0.425***	18.271***	-0.055**	10.290	-0.425***
	(0.015)	(0.026)	(0.026)	(0.097)	(7.054)	(0.026)	(8.770)	(0.097)
Observations	14,765	30,525	13,772	27,595	30,525	30,525	27,595	27,595
R-squared	0.974	0.576	0.943	0.491	0.976	0.576	0.970	0.491
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Case FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: This table reports coefficient results from difference-in-differences regressions. Panel A is the results for plaintiffs and Panel B is the results for defendants. The dependant variable is the Patent Index (PI), the sum of number of patents in each technology class scaled by the average number of patent shares in the same technology class. Concentration Index(CI) is calculated as a sum of patent shares in each technology class. The variable, number of patents is included as a control. *Treat* equals one when the pair is plaintiff-defendant match, and zero for controls. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.

A.5: Intensity and magnitude of patent - Control group 3

	LP technology sector				Non-LP technology sector			
	Panel A: Plaintiffs		Panel B: Defendants		Panel A: Plaintiffs		Panel B: Defendants	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PI_{LP}	CI_{LP}	PI_{LP}	CI_{LP}	PI_{-LP}	CI_{-LP}	PI_{-LP}	CI_{-LP}
Treat x Post litigation	-0.095***	-0.017	-0.044	-0.059**	30.406	-0.017	-5.845	-0.059**
	(0.024)	(0.020)	(0.028)	(0.028)	(27.310)	(0.020)	(40.977)	(0.028)
Observations	39,414	39,414	35,017	35,017	39,414	39,414	35,017	35,017
R-squared	0.543	0.516	0.487	0.537	0.894	0.516	0.883	0.537
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Case FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: This table reports coefficient results from difference-in-differences regressions. Panel A is the results for plaintiffs and Panel B is the results for defendants. The dependant variable is the Patent Index (PI), the sum of number of patents in each technology class scaled by the average number of patent shares in the same technology class. Concentration Index(CI) is calculated as a sum of patent shares in each technology class. The variable, number of patents is included as a control. *Treat* equals one when the pair is plaintiff-defendant match, and zero for controls. Standard errors are clustered at case level and are reported in parentheses. *, **, and *** denote significance at 10%, 5% and 1% level, respectively.